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ASSESSING THE SPATIAL DISTRIBUTION OF CROP PRODUCTION USING A CROSS-ENTROPY METHOD

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ABSTRACT

While agricultural production statistics are reported on a geopolitical – often national - basis we often need to know the status of production or productivity within specific sub-regions, watersheds, or agro-ecological zones. Such re-aggregations are typically made using expert judgments or simple area-weighting rules. We describe a new, entropy-based approach to making spatially disaggregated assessments of the distribution of crop production. Using this approach tabular crop production statistics are blended judiciously with an array of other secondary data to assess the production of specific crops within individual 'pixels' – typically 25 to 100 square kilometers in size. The information utilized includes crop production statistics, farming system characteristics, satellite-derived land cover data, biophysical crop suitability assessments, and population density. An application is presented in which Brazilian state level production statistics are used to generate pixel level crop production data for eight crops. To validate the spatial allocation we aggregated the pixel estimates to obtain synthetic estimates of municipio level production in Brazil, and compared those estimates with actual municipio statistics. The approach produced extremely promising results. We then examined the robustness of these results compared to short-cut approaches to spatializing crop production statistics and showed that, while computationally intensive, the cross-entropy method does provide more reliable estimates of crop production patterns.

Key Words: Entropy, cross entropy, remote sensing, spatial allocation, production, crop distribution

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1. INTRODUCTION AND RATIONALE

Internationally comparable series of annual crop production data are available at a national scale from FAO and USDA. While very rich in their commodity coverage, these data give no clue as to the geographic distribution of production within country boundaries. Periodic attempts at compiling sub-national data have been made by, for example, centers of the CGIAR (e.g., Carter et al. 1992; CIAT 1996; CIP 1999; Ladha et al. 2000; ILRI 2001; IFPRI 2001), by FAO (Gommes 1996), and by the Famine Early Warning System (FEWS) in parts of Africa (http://www.fews.net). With the exception of the on-going mandate of FEWS to compile sub-national agricultural production and market data in many parts of sub-Saharan Africa, all of these were limited, one time efforts. The enormous gaps in the geographic, time period, and crop coverage of sub-national data collections are unlikely ever to be filled. But even where sub-national data are available, they are often still inadequate in terms of providing sufficient spatially disaggregated insights into the location of production. Obtaining sub-national agricultural production data for, say, Lampung province in Indonesia, the state of Rondonia in Brazil, or the Valle de Cauca department in Colombia, would still reveal nothing about spatial variability of production within those areas of many thousand square kilometers. Yet to compile all such data globally, or even regionally, represents a formidable data discovery

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and harmonization challenge.[2] To address this situation, the approach described in this paper seeks to generate plausible estimates of the distribution of crop production at the scale of individual pixels (notionally of arbitrary scale but in this application of some 80 km^2), through judicious triangulation amongst a range of accessible evidence. If spatial disaggregations can be made with some confidence, we remove one of the major analytical weaknesses of meso- and macro-scale agricultural studies – the inability to objectively re-aggregate production statistics into any other geography than the national or sub-national administrative boundaries for which published statistics exist. This has been a thorn in the flesh of the most attempts to analyze production and productivity by agro-ecological zones or watersheds, e.g., the agricultural research priorities study of Davis, Oram, and Ryan (1987), the CGIAR's Regional AEZ strategies of the 1990s (TAC 1992), the global food perspective studies of FAO (Alexandratos 1996; Bruinsma 2003), and IFPRI (Rosegrant et al. 2001), and agroecosystem assessments (e.g., Wood, Sebastian, and Scherr 2000).

With proper ground-truthing it is technically feasible to discriminate the cultivation of some types of crops or production systems, such as paddy rice, plantations, and orchards, using high-resolution satellite imagery. In temperate regions it is also easier to detect areas under annual crop cultivation that lie fallow during the cold/dry seasons. But national land cover mapping studies usually discriminate only "cropland" at best, and instead focus on the delineation of types and sub-types of "natural" ecosystems that are often more homogeneous over larger physical extents, and of more direct interest to the

[2] A particular challenge is to compile regional estimates of the spatial variation of crop production using national agricultural surveys and censuses. While such surveys typically allow for greater spatial resolution of crop distribution, the sampling frameworks employed still limit the spatial scale at which results can be generated within acceptable levels of statistical confidence, and they are seldom carried out at less than ten year intervals.

forestry, wildlife, or environmental agencies who usually undertake such work. The global 1km land cover database (IGBP 1998) does contain some crop-specific agricultural land cover interpretations in its regional and pre-classified background data (the *Seasonal Land Cover Regions*), but they are few and inconsistently applied. This global dataset does, however, provide a relatively detailed picture of where (undifferentiated) croplands may be found, and this serves as the first approximation of the spatial boundaries within which our crop-specific distribution takes place.

Figure 1--The task of spatial crop allocation

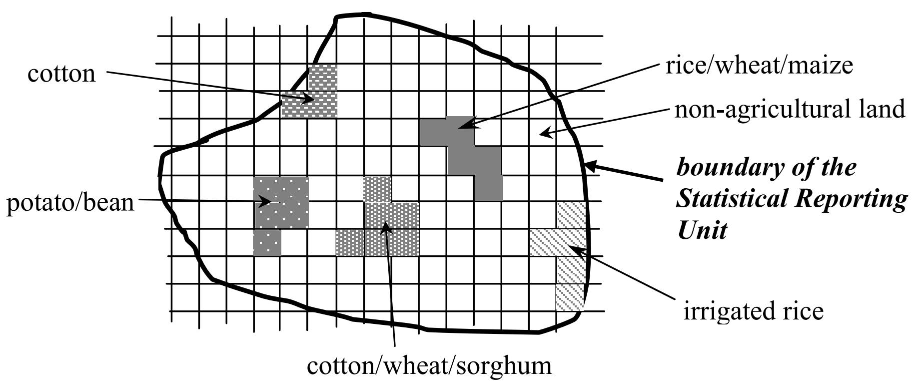


Figure 1 shows, diagrammatically, the challenge faced by the spatial allocation approach. The bold closed-curve shows the boundary of the geographical area within which we wish to make a plausible assessment of the spatial patterns of production of individual crops. These areas are typically the administrative (geopolitical) statistical reporting units (SRUs) for which we have been able to obtain production statistics, and may be national or sub-national e.g. states, departments, districts, or counties. The SRU is divided into many grid cells (pixels) whose actual sizes depend upon the resolution of key spatial data layers such as land cover, but that typically range from 500m x 500m to 10km x 10km for regional studies. Armed with production statistics for each SRU, the task of the spatial allocation model is to distribute the reported production of individual crops amongst the pixels so as to best imitate the "real-world" production geography. Some pixels may be allocated no crops, others only a single crop, while the remainder will contain multiple crops.

The paper is organized as follows. The next section describes the types of information we use in the spatial allocation process. Section 3 introduces the allocation approach – the cross-entropy method. In this section we first introduce the entropy concept, and then describe the spatial allocation model in detail. Section 4 applies our model to data compiled for Brazil, a very large and agroecologically diverse country. We then describe the application of the model and evaluate the accuracy of the allocation results. In addition, we also compare the current model with simpler crop allocation methods. Section 5 discusses the results and describes on-going efforts to further develop the spatial allocation model.

2. INFORMATION USED TO ASSESS THE SPATIAL DISTRIBUTION OF PRODUCTION

The goal of the allocation is to spatially disaggregate SRU tabular statistics and assign them to specific "pixels" within a gridded map of the SRU. The information used to guide the spatial allocation comes in various forms.

1. *Crop production statistics.* The data include the harvested areas, production, and average yield for each crop being included in the allocation exercise. This tabular data is derived from international or national sources (e.g., FAOSTAT for national SRUs, national statistical yearbooks for first administrative level SRUs, and agricultural surveys for second level SRUs)

2. *Production system structure.* Agricultural production is diverse in terms of farming technology and the scale of the farm enterprise. Commercially-oriented farmers tend to use more and higher quality production inputs such as high-yielding varieties, mechanization, irrigation, fertilizers, pesticides, credit and market information, while subsistence farmers often rely only on traditional cultivars, manual labor, and limited application of organic nutrients. The intent of partitioning the reported crop production amongst production system types is to provide some criteria that may help guide the assessment of specific production locations and yield variability within the SRU. Information is gathered to allow the partitioning of total reported production into three components: irrigated, rainfed – commercial, and rainfed – subsistence. Information to support the partitioning of production for each crop and for each SRU is gathered on an ad hoc basis from a diverse mix of sources such as small-scale and farming system studies, country reports, agriculture survey data and often expert opinion.
3. *Cropping intensity.* Most production statistics report crop areas in terms of the area harvested. From a spatial allocation perspective and for consistency with satellite-derived estimates of cropland, we must convert harvested to physical crop areas. Cropping intensity is defined as the ratio of the harvested area to the physical area on which crops are grown, usually in the context of an annual cropping cycle. For example the irrigated rice fields of a region might be planted twice and produce two crops per year. Thus the 100,000 hectares of harvested rice reported for the SRU are obtained from just 50,000 hectares of land. Similarly, maize and beans may be grown in a single season rotation. Thus 50,000 hectares

of maize-bean fields will produce 50,000 hectares of both maize and beans during a given year. For each crop we assess the likely cropping intensity based on available secondary data and expert opinion.

4. *Cropland extent:* We reclassify available satellite-derived land cover imagery so as to better assess the likely share of cropland in each individual pixel. Land cover is the most important source of data for identifying the geographic areas within which the crop allocation takes place. By default crop production is only allocated within the extent of cropland.[3].

5. *Biophysical Suitability for Crop Production.* The patterns and intensities of crop production are influenced, often significantly, by biophysical conditions. There are many ways to assess the biophysical suitability of a given location for crop production; from simple rules of thumb based on a single factor such as annual rainfall, to crop-specific process models that simulate crop growth on a daily basis using many climate, soil, plant, and management variables. For our purposes we adopted a globally consistent assessment approach initially developed by FAO (1981). FAO developed sets of crop-specific rules that used location-specific data on elevation, temperature, and rainfall data in order to assess the agro-climatic suitability of fifteen globally-important crops under low- and high-input rainfed conditions (FAO, 1981). This approach has since been extended in many ways including; irrigation as well as rainfed suitability, additional crops, consideration of the influence of slope and soils, and progressively more elaborate suitability assessment algorithms (FAO 1984, FAO/IISA 2000). We utilized the most recent

[3] There is sometimes a need to relax this constraint if the statistical data call for more cropland to be found than is depicted in the land cover data. Thus, we treat the statistical data as having a higher level of confidence than the land cover data.

versions of the crop suitability data available as a 5 minute (approximately 9kmx9km) grid globally (Fischer et al. 2000). From this dataset we utilized the irrigated, “high” input/technology rainfed, “low” input/technology global crop suitability data that include both suitable areas and potential yields.

6. *Existing crop distribution maps.* Any existing mapped data of the spatial distribution of individual crops based on direct field observation is a very valuable information source. Our “a priori” assessment of the likely distribution of individual crops is given a high weight in the allocation procedure. Thus, any credible source of information on existing crop distribution, even if it is only partial in its geographic coverage, helps improves our “priors” and ultimately the final allocation outcomes.

3. CROSS ENTROPY APPROACH

All the above information can be brought to bear on the spatial allocation of agricultural production in one way or another. But we need an analytical approach that can utilize all such information, while recognizing that each piece may be limited, partially correct, and sometimes conflicting with other input data sources. Golan, Judge and Miller (1996) proposed various estimation techniques based on the principles of entropy to tackle such problems. Zellner (1988) described the advantage of the entropy approach as satisfying the “information conservation principle”, by neither ignoring any relevant input information nor injecting any false information (Robinson et al. 2000). This principle is highly compatible with our triangulation approach.

Specifically, the spatial allocation model uses a cross entropy (CE) approach that allows for the inclusion of prior knowledge about actual crop distribution or about factors that influence such distribution. Using this methodology to disaggregate crop production statistics within any particular SRU, it is straightforward to apply constraints that ensure that allocated crop areas are non-negative and that they sum up to the total area reported for each crop for the entire SRU. The approach is also flexible in supporting the inclusion of additional equality or non–equality constraints that reflect the distribution of factors influencing the spatial patterns of crop production.

INFORMATION ENTROPY

The cross entropy formulation is based upon the entropy concept in information theory originated by Shannon (1948). For a given probability distribution $\{p_1, p_2, \ldots, p_k\}$, Shannon's information entropy (amount of information) is defined as

$$H(p_1, p_2, \ldots, p_k) = -\sum_{i=1}^{k} p_i \ln p_i \tag{1}$$

where *ln0=0* by convention, which means zero probability yields zero information.

Jaynes (1957) proposed a principle of maximum entropy to identify an unknown distribution of probability from given moment constraints. Kullback (1959), Good (1963) introduced the notion of cross-entropy, *CE*, which is a measure of the discrepancy between the two probability distributions, say p_i and q_i.

$$\begin{aligned} & CE(p_1, p_2, \ldots, p_k, q_1, q_2, \ldots, q_k) = \sum_{i=1}^{k} p_i \ln(p_i / q_i) = \sum_{i=1}^{k} p_i \ln p_i - \sum_{i=1}^{k} p_i \ln q_i \\ & = -H(p_1, p_2, \ldots, p_k) - \sum_{i=1}^{k} p_i \ln q_i \end{aligned} \tag{2}$$

The cross entropy minimization approach provides a model formulation in which the discrepancies between **p** and its prior, **q,** are minimized subject to certain constraints.

SPATIAL ALLOCATION MODEL

Here we define our spatial crop allocation problem in a cross entropy framework. We first convert the reported harvested area, $HarvestedArea_j$ for each crop, j, into an equivalent physically cropped area, $CropArea_j$, using an estimated average cropping intensity, $Cropping\ Intensity_j$.

(3a) $$CropArea_j = HarvestArea_j / CroppingIntensity_j$$

To capture some measure of the heterogeneity of production we distinguish amongst different types of production systems. Different farmers might produce crops using quite different levels and mixes of production inputs, and these differences have important consequences for crop performance. In the current model, we allow for each crop to be disaggregated into three distinctive production systems , namely; *irrigated*, *high-input rainfed*, and *low-input rainfed* (e.g. total rice production is split into irrigated rice, high-input rainfed rice and low-input rainfed rice shares). These three types of production system were selected so as to correspond with the assumptions used to derive the three crop suitability surfaces described above. Let s_{ijl} be the share of the cropped area of crop j in production system, l, allocated to pixel i, and since $CropArea_j$ is the total physical area for crop j, the area allocated to pixel i for crop j, A_{ijl}, is

(3b) $$A_{ijl} = CropArea_j \times Share_{jl} \times s_{ijl}$$

where $Share_{jl}$ is the share of total physical area for crop j in production system l .

In general we have some prior knowledge or intuition about crop-specific area distributions. Let π_{ijl} represent our prior assessment of the area shares pixel i and crop j in production system l. The prior can be based upon an examination of existing crop distribution maps, on expert judgement, or any other information deemed relevant. For example, one could generate a crop distribution *a priori* using the biophysical and social-economic attributes of each location. The minimum cross entropy formulation seeks to a derive a set of area shares s_{ijl}, such that

(4) $$\underset{\{s_{ijl}\}}{MIN} \quad CE(s_{ijl},\pi_{ijl}) = \sum_i \sum_j \sum_l s_{ijl} \ln s_{ijl} - \sum_i \sum_j \sum_l s_{ijl} \ln \pi_{ijl}$$

subject to:

(5) $$\sum_i s_{ijl} = 1 \quad \forall j \forall l$$

(6) $$\sum_j \sum_l CropArea_j \times Share_{jl} \times s_{ijl} \leq Avail_i \quad \forall i$$

(7) $$CropArea_j \times Share_{jl} \times s_{ijl} \leq Suitable_{ijl} \quad \forall i \forall j \forall l$$

(8) $$1 \geq s_{ijl} \geq 0 \quad \forall i, j, l$$

where:

i : *i = 1, 2, 3, ...,* are the pixel identifiers within the SRU,

j: *j = 1, 2, 3, ...,* are the crop identifiers,

l: *l = irrigated, rainfed-high input, rainfed-low input,* are the specific production system conditions under which each crop might be produced.

$Avail_i$: total cropland in pixel i, as estimated from land cover data described in the previous section.

$Suitable_{ijl}$: the suitable area for crop j at input level l in pixel i, extracted from the FAO/IIASA global crop suitability surfaces described in the previous section.

The objective function for the spatial allocation model is defined so as to minimize the cross entropy measure between the estimated area shares, s_{ijl}, and our prior estimates, π_{ijl} . Equation (5) is simply the "adding-up" constraint that ensures we allocate exactly the amount of crop area reported for the SRU. Equation (6) is the land cover constraint whereby the actual cropland area share of pixel i derived from the land cover data is set as the upper limit for the area to be allocated for crop production within each pixel. Equation (7) is the constraint ensuring that the area allocated for production of a specific crop within a pixel cannot exceed the area deemed as suitable for such production within the pixel. The last equation, equation (8) simply establishes the feasible range for the value of individual crop area shares. As we can see, the essence of this classic CE approach is to use any and all credible sources of information to make our best prior assessment of where crops are actually being grown. The criterion for choosing the solution (out of many possible solutions because the problem is under-determined) is to minimize the entropy-based divergence from the prior.

Obviously, an informative prior distribution for each crop is quite important for the success of the model. If such information already exists, e.g. dot maps of the actual distribution of specific crops, these can be incorporated. However, this is a luxury we are seldom afforded, and we must make do with only partial information (in terms of both crop and geographic coverage). In most cases, however, we use other simple approaches. The most commonly used short-cut methods of portraying production data spatially are to uniformly distribute production across the total land area or across only the cropland area. Since, however, we believe that individual commodities are more likely to be cultivated in areas in which they have some comparative advantage, we can also draw on results from analyses of the spatial variability of crop production potential. We use the FAO/IIASA surfaces described above because they provide assessments not only of the suitable area by crop and production system (as used in equation 7), but also of the associated potential yields.

Our strategy to develop priors involved several elements. The first was to partition total production in each SRU amongst the three possible production systems (irrigated, rainfed-high input, and rainfed-low input). For each system, the total production was allocated amongst pixels falling within the cropland extent in proportion to their relative potential yield[4] and population density. Weighting by population density acknowledges that many areas potentially suitable for crop production are not actually exploited for a range of reasons. Particularly for the type of subsistence agriculture practiced in many developing countries, however, production is likely to be greater (and more intensive) where local demand and labor (rural population densities) are higher. To reduce incentives for production to be allocated into urban areas the population density map was truncated to zero at levels typically associated with settlement and urbanized areas.[5] Thus, we derived our prior crop distribution shares, π_{ijl} , using normalized potential yields for crop *j* at input level *l* and pixel *i, $Suitability_{ijl}$,* and normalized, truncated population density in pixel *i*, $Popdens_i$, as follows:

$$\pi_{ijl} = \frac{Suitability_{ijl} \times Popdens_i}{\sum_i Suitability_{ijl} \times Popdens_i} \quad \forall j \forall i \forall l \tag{9}$$

For the case of purely subsistence production systems, crop distribution priors might also be determined using only the relativities of rural population density within the extent of cropland.

4. MODEL APPLICATION

We apply the above model to Brazil, a very large and diverse country with a total land area over 8.5 million square kilometers. Brazil is rich in natural resources and biodiversity and heterogeneous in agroecological and socio-economic conditions, with quite different types of farming systems being found within its boundaries. While, on the

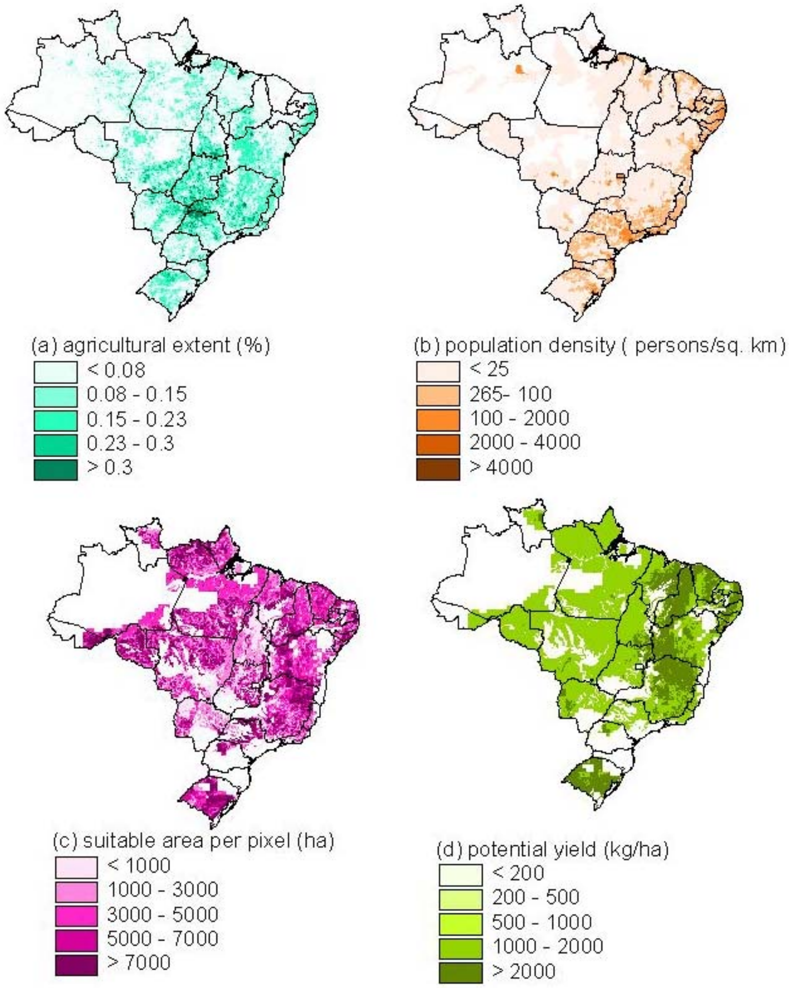
[4] Recalling that individual potential productivity maps were available for each crop and production system combination

[5] Although land cover classification systems differentiate between urban and cropland areas, in practice only the larger and more built-up urban areas are systematically assigned to the urban class. We thus need to exclude from areas delineated as croplands those areas where population density is so high that production options for most crops are limited.

average, only 6 percent of the land area is cropland, there are vast tracts of forest and savannas with little or no agriculture, as well as areas such as the central “cerrados” and the south where landscapes are almost entirely agricultural. This wide range of agricultural systems and spatial intensity of production is valuable for the purposes of testing the spatial allocation approach.

Brazil’s first level administrative units are “states”, and at the third level “*municipios”*. Though there are only 27 states, there are over 4,490 *municipios* in Brazil, averaging over 160 *municipios* per state. The spatial resolution of the land cover pixels used in the application is 5 by 5 arc minutes, and each pixel of this resolution represents just over 9*km* by 9*km* (around 8,500 hectares) at the equator. Brazil comprises over 100,000 pixels of that size. Figure 2 shows maps of some of the key spatial datasets used for the analysis. Cropland is expressed as the proportion of each pixel occupied by cropland, as shown in Figure 2(a). This dataset is derived from the 30 arc second (approximately 1-km) resolution global land cover database developed by the EROS DATA Center of the U.S. Geological Survey using methods described by Wood, Sebastian and Scherr (2000) and Ramankutty and Foley (1998). We calculate the actual cropland area in each pixel by taking account of the change of physical pixel size with latitude. Figure 2(b) is the population density map. We set average population density limits of 5 $persons/km^2$ and 500 $persons/km^2$ (within a cropland pixel extent of around 81 km^2) as defining those areas in which crop production would be allocated. As pointed out in Section 2, FAO/IIASA’s newly developed crop suitability surfaces are rich sources of information on both potential yields and suitable areas for each commodity under different management/input assumptions. FAO/IIASA suitability surfaces are defined for five production system types for each crop: rainfed - high input, rainfed – intermediate input, rainfed – low input, irrigated – high input and irrigated – intermediate input. In accordance with our model specification, we omitted the two intermediate input classes and represent production conditions by just three possible production systems classes: high-input rainfed, low-input rainfed and high-input irrigated (referred to henceforth as irrigated). We defined suitable areas within each pixel as the sum of the following four suitability classes in the original FAO/IIASA suitability database: very suitable, suitable, moderate suitable and marginal suitable. Accordingly the mean potential yield across the suitable area of each pixel is calculated as the area-weighted average of the potential yields estimated for the above four suitability classes. As an example, Figure 2(c) shows the suitable areas of low-input rainfed maize and Figure 2(d) the potential yield distribution of low-input rainfed maize.

Figure 2 Cropland, population density and suitability maps for maize



The following eight crops are included in the spatial allocation model for Brazil: rice, wheat, maize, cassava, potato, beans and soybean. Collectively, these eight crops account for nearly one quarter of the value of Brazilian agricultural output in 2000, and nearly half of all crop output (Alston et al. 2000). The reference year of the spatial allocation is 1994, the year in which the satellite land cover imagery was collected. We derive 1994 production statistics by taking a mean of the annual values for 1993-95. The allocation units (the SRUs) are the 27 states in Brazil. Starting with the tabular production statistics by state (see Table 1 for the harvested areas), we first disaggregate into the three production systems based on the area shares given in Table 2. These shares were compiled from a mixture of statistical data, other secondary data sources and expert opinion. Table 2 shows the percentages of irrigated and high-input rainfed areas for all eight crops in the 27 states of Brazil, the percentage of low-input rainfed area being the residual. The next step is to convert harvested areas into physical land areas using crop and production system specific cropping intensities. Some crops, in particular irrigated crops such as rice, are multiple-cropped in many regions. In such cases the physical crop area is calculated by dividing the harvested area by its corresponding cropping intensity (Equation (1)). As with production system shares, cropping intensity estimates by crop and production system were compiled from available data sources, relying heavily on expert knowledge of specific cropping patterns practiced across Brazil.

From a modeling perspective, the disaggregation into irrigated, high-input rainfed and low-input rainfed production systems resulted in 24 distinct production systems (3 systems * 8 crops) being submitted to the spatial allocation process.[6]

[6] In order to inject the necessary level of competition for land amongst crops, we aggregated the area of all other crops in the state level statistics into a single notional "Other crop", to which we assigned the generic suitability qualities of low-input rainfed maize. This additional crop was also part of the allocation process such that the total area of crops allocated (across the 8 specific crops and the "Other" crop) was equal to the total amount of cropland in the state.

Table 1--Harvested areas by states of Brazil: 1993-95

State	Wheat	Rice	Maize	Sorghum	Potato	Cassava	Bean	Soybean
				(Hectare)				
Brazil	**1,267,967**	**4,403,820**	**13,191,061**	**138,991**	**169,681**	**1,868,646**	**4,783,341**	**11,268,031**
Acre		34,051	36,402			22,270	15,256	
Alagoas		7,335	70,578			30,534	110,775	
Amapa		586				2,559		
Amazonas		3,223	4,423			34,930	2,672	
Bahia		57,089	428,296	17,929	1,433	249,724	583,680	428,119
Ceara		67,045	507,781	365	11	116,276	548,077	
District Federal	778	2,058	20,253	81	462	495	5,598	46,149
Espiritu Santo		26,576	100,869		646	20,621	67,139	
Goias	3,093	289,420	842,786	31,019	276	17,759	142,947	1,070,754
Maranhao		759,309	602,078			261,855	116,897	64,778
Mato Grosso		461,965	404,532	18,281		24,315	39,646	2,005,885
Mato Grosso do Su	48,360	99,552	410,283	1,042	11	27,570	35,778	1,069,634
Minas Gerais	4,110	375,871	1,487,266	9,417	30,773	77,313	531,982	580,839
Para		204,696	245,100			266,333	81,067	
Paraiba		7,180	173,552	24	957	41,987	192,298	
Parana	646,682	108,955	2,647,208	164	43,050	147,792	559,837	2,142,562
Pernambuco		5,284	232,759	962	249	85,630	261,661	
Piaui		269,344	401,136	12		94,623	288,078	7,286
Rio Grande do Nor		1,758	97,821	3,417		47,691	127,176	
Rio Grande do Sul	471,334	983,221	1,782,287	28,660	45,792	107,934	208,633	3,086,668
Rio de Janeiro		17,043	26,812		175	13,781	11,913	
Rondonia		143,690	193,290			38,175	147,854	4,861
Roraima		8,783	6,479			2,655	1,578	
Santa Catarina	58,227	149,866	1,040,708		18,947	53,200	354,897	213,873
Sao Paulo	35,382	146,696	1,300,673	27,618	26,842	31,996	279,462	524,341
Sergipe		6,466	56,828		57	40,754	59,541	
Tocantins		166,758	70,860			9,875	8,897	22,283

Source: IFPRI (2001), and EMBRAPA

Table 2—Share of crop area under different farming system in Brazil: 1993-95 (percent)

State	Irrigated Area*								High-input Rainfed Area*							
	Wheat	Rice	Maize	Sorghum (%)	Potato	Cassava	Bean	Soybean	Wheat	Rice	Maize	Sorghum (%)	Potato	Cassava	Bean	Soybean
Acre											89			63		
Alagoas											26	100		16		
Amapa											86			63		
Amazonas											40			35		
Bahia		2	10	0	100				100		50	85		41	10	95
Ceara		16									40	89		40	0	
District Federal	100				70		23			100	98			54	15	100
Espiritu Santo					30						71			76	10	
Goias	60	2			70		29		40	20	98	100		87	14	99
Maranhao		1								99	39	100		20	0	97
Mato Grosso							20			70	97	100		74	0	99
Mato Grosso do Su		65							98	7	97			74	10	99
Minas Gerais	100	39			40		11			49	84	98	36	66	9	95
Para									80		86			63		
Paraiba											48	99		19		
Parana		19			80		5		90	24	71	91		53	19	97
Pernambuco					5						41	97		21	0	
Piaui		4								10	45	99		45	0	95
Rio Grande do Nor		76			50					24	76	99		36	10	
Rio Grande do Sul		79									59	98		43	0	
Rio de Janeiro		99			50				85		64	95		41	10	95
Rondonia									100		73	99		76		
Roraima		57									95	100		81		
Santa Catarina		92			60				78	2	58	90		42	20	90
Sao Paulo					70		24		96	100	91	99		65	15	97
Sergipe		70			100					30	56	98		12		
Tocantins		34									96	100		93		98

Source: compiled by authors from a variety of statistical sources and expert opinions
*Note: Balance of production shares from each state are included in "low input rainfed" system

All the spatial allocation input data components for each state were assembled in the above manner and submitted for optimization on a state-by-state basis. Each optimization run attempts to simultaneously allocate all 24 production system (plus the "other crop" category that accounts for the balance of cropland use) into pixels across the entire state subject to the defined constraints, using the prior distribution as its starting point. GAMS (GAMS 2002) is used to solve the optimization problem[7]. The output is the area in hectares of each production system in each pixel in the state (including pixels where no production was assigned). Figure 3 shows the pixel level spatial allocation of the eight crops for Brazil, compiled from the individual state level, production system results.

The intent of the spatial allocation model is not to try to match the real world pixel by pixel, but rather to derive a substantially more informative picture of the likely distribution of the production of individual crops than the state levels statistics alone can reveal (e.g the maps are an attempt to "spatialize" Table 1). We can see from Figure 3 that the allocation approach generates quite diverse patterns of crop distribution among and within the states. As well as providing richer insights into the distribution of production within very large geopolitical units, the pixel-level results can be aggregated into any other geography of interest, e,g, watershed or agro-ecological zone, for further analysis.

[7] The size of optimization problem is very large due to large number of pixels within many states, and a high-performance solver is needed. In the current optimization, we use GAMS newly-developed PATHNLP solver.

Deleted: states

Figure 3—Predicted spatial patterns of crop production

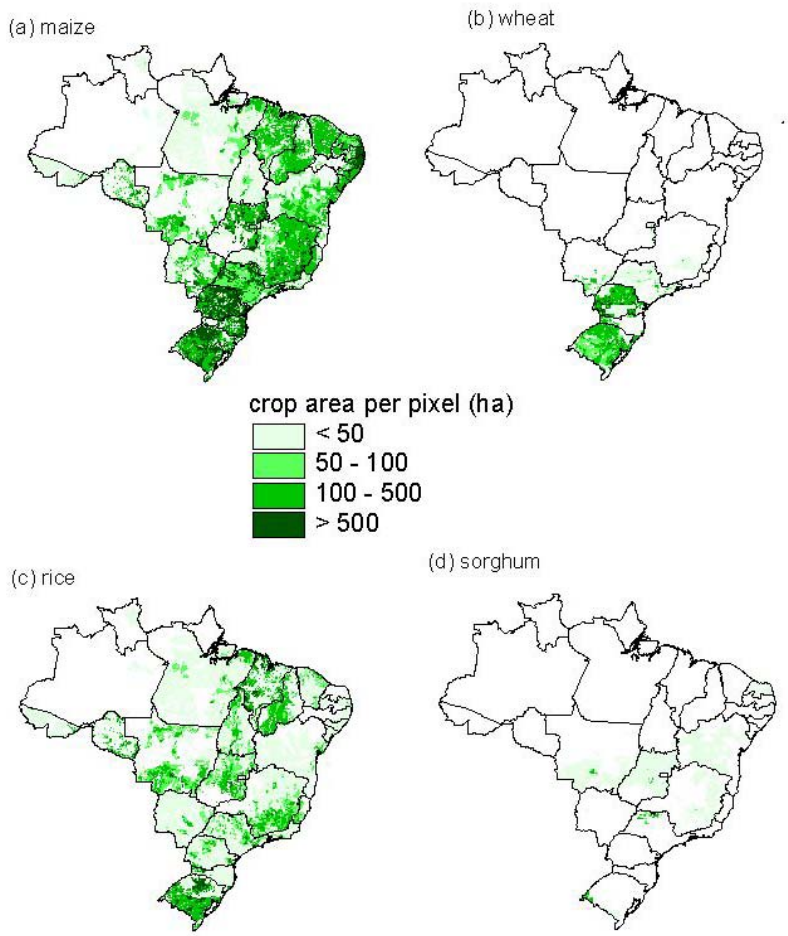
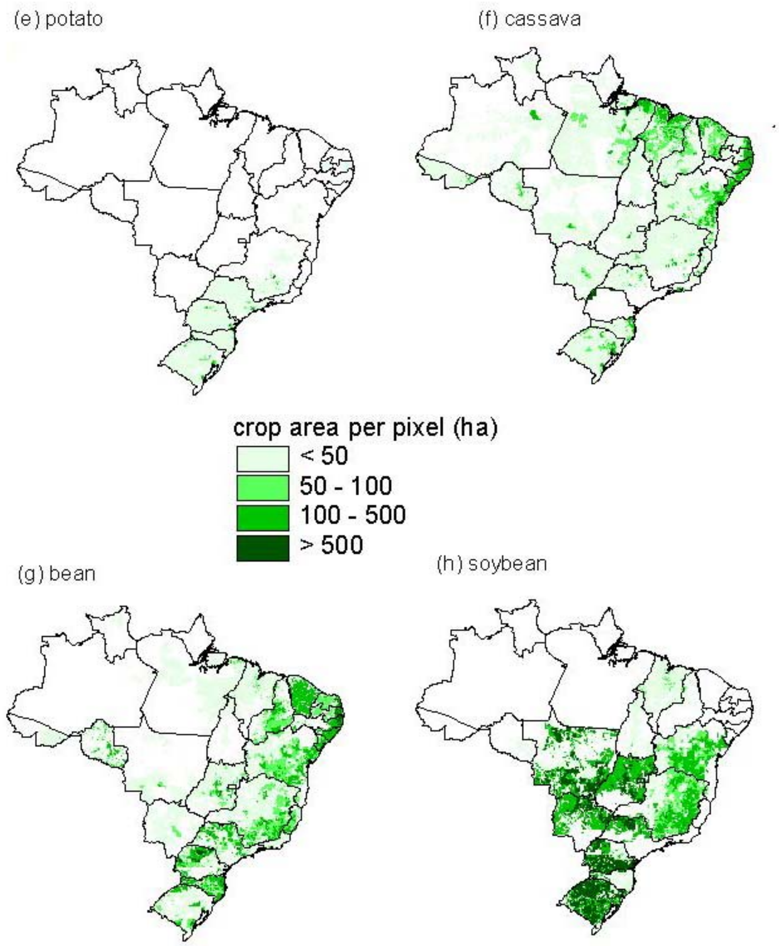


Figure 3—Predicted spatial patterns of crop production (continued)



5. MODEL VALIDATION AND COMPARISON

To assess how well the approach performs, we aggregate the over 100,000 pixel level results into the 4490 *municipios* of Brazil for which we have a separate database which includes data on six of the allocated crops: maize, rice, wheat, beans, cassava and soybean. We compare these synthetic municipal area estimates with the actual municipal production area statistics[8]. Figure 3 shows the graphical results of this comparison, in which the horizontal axis is the actual municipal statistics while the vertical axis are the estimates derived by aggregating the pixel level allocation of state statistics. The spatial allocations for wheat, maize and bean match the municipal statistics well, with R^2 values all greater than 0.50 (0.65, 0.54. and 0.53, respectively). For these three crops, the points clearly cluster around the 45 degree line of perfect correspondence. For the other three crops, however, the data points are more dispersed. The R^2 values for cassava, rice and soybean are 0.47, 0.43, 0.40, respectively.

There are several factors that help account for the differences between observed and predicted municipal crop areas. Perhaps the most fundamental is the simplicity of the method used to assign the crop area priors relative to the complex web of factors involved in farmers' choices of crops, crop mixes and the type and scale of production methods. But there are also many data issues. As the data for each state was compiled, inconsistencies amongst data layers surfaced. A logical set of assumptions embedded in the methodology is that the physical area required to produce the reported harvested amount of crops is less than or equal to the extent of cropland, and that within the cropland area sufficient, non-overlapping suitable areas could be found for each crop. In a significant number of cases this logic was belied by the available data. There are at least four sources of mismatch amongst data sources: unreliable estimates of cropland extent; cropping intensity estimates that do not fully capture the land-saving benefits of multi-cropping strategies, particularly within a single growing season; biophysical suitability interpretations that do not match location specific conditions, nor the reality

[8] Before this comparison was made, the area values of each municipio were scaled by a fixed factor, the ratio of the reported state crop area to the sum of the reported municipal crop areas. This was done to eliminate discrepancies between the state and municipal statistics as a source of error.

that production may be economically viable and important for food security, even at relatively low levels of biophysical suitability and, finally but significantly, the reliability of the production statistics themselves. Where data inconsistencies lead to infeasible conditions, a set of rules was devised to progressively relax the constraints until the allocation could be completed successfully.[9]

From a methodological perspective a key issue is the very heavy dependence on generating good initial priors of actual crop distribution, after which the constraints imposed in the optimization are largely to ensure proper accounting of the various area components, and to resolve competition amongst crops for available, suitable land. This feature of the CE approach provides some useful flexibility, for example, to include less rigorous sources of input data such as dot maps of crop location or expert knowledge about where specific crops are grown, but that flexibility comes at the cost of requiring a significant amount of data to be compiled and interpreted at the pre-optimization phase.

As described in section 3 the algorithm used for assigning the prior relies on potential yields (taken from the crop suitability database) and population density. While this has the advantage of pragmatism in terms of available data and some theoretical underpinnings, it falls short of an ideal approach. One characteristic of this ideal would be to include a more explicit economic focus, but this would involve another level of data discovery and compilation challenges. We have examined including crop prices in the algorithm and generating priors on the basis of nominal gross revenues (potential yield x

[9] For example (1) if insufficient suitable area can be found within the cropland extent, the share of suitable area in each pixel in the extent is increased in steps, up to a maximum of the share of cropland in each pixel, and (2) if there is insufficient land within the cropland extent for the total crop area to be allocated, the cropland area is expanded incrementally into adjacent suitable areas. These rules were developed in applying an earlier prototype of the approach to spatial allocation of the same eight crops for the LAC region (Sebastian and Wood 2000).

price). But this approach only proves effective if the priors are computed by considering potential competition amongst crops at the pixel level. While this is perhaps more realistic from the perspective of a commercial farming environment, weights other than prices might be more appropriate for other production goals, e.g. nutrition content for goals of food security. Empirical observation of subsistence farmer crop selection practices suggest that production of preferred basic food staples often takes place with little regard to biophysical suitability. But assembling information on household production goals and strategies, and local dietary preferences was beyond the scope of this pilot work. Since our own interests lie in developing a framework that can be applied in a regional and even global context, we seek to develop methods that minimize reliance on data that is fragmentary and expensive to compile. Nevertheless, there certainly appears scope as we develop this approach to add further layers of sophistication into the process of assigning priors.

As things now stand, the potential suitability data (both suitable area and potential yields) are the most significant driving force in determining the spatial variability of production within the cropland extent, since they are used both in the priors (potential yields) and in the optimization constraints (suitable areas).

Figure 4--Correlation of municipal production statistics and predictions made from the spatial allocation model: Brazil 1993-95

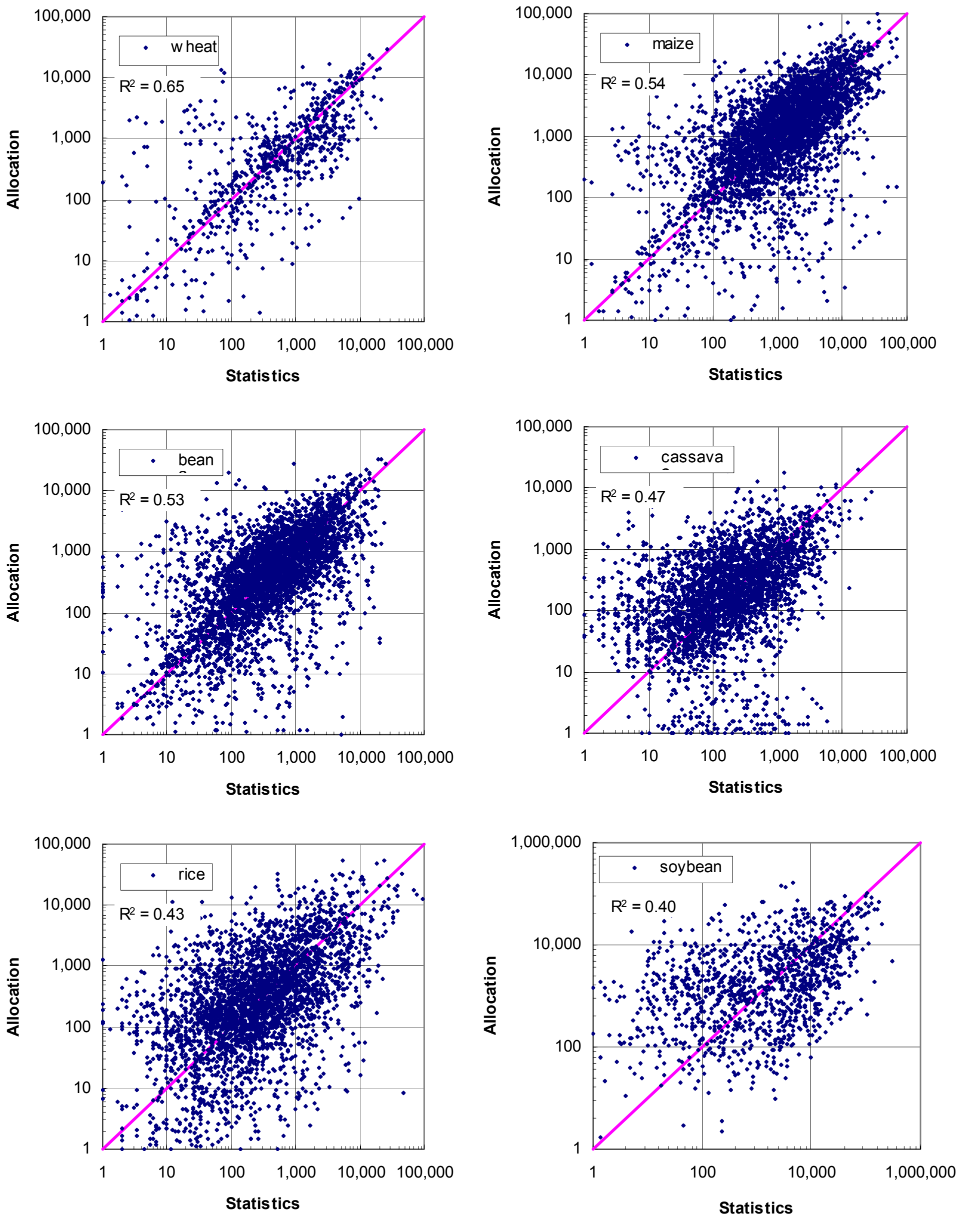


Table 3--Comparison of the effectiveness of alternative spatial allocation methods

Allocation Methods	Explained Variance					
	wheat	rice	maize	cassava	bean	soybean
Land Area Shares	0.26	0.31	0.47	0.38	0.40	0.27
Suitable Area Shares						
Low Input	0.17	0.31	0.22	0.32	0.26	0.11
High Input	0.37	0.34	0.37	0.37	0.35	0.08
Irrigated	0.0	0.32	0.01	0.45	0.13	0.0
Mixed (weighted)	0.15	0.38	0.17	0.39	0.28	0.04
Cropland Shares	0.38	0.31	0.44	0.38	0.25	0.37
Cross Entropy	**0.65**	**0.44**	**0.54**	**0.47**	**0.53**	**0.40**

Despite the seemingly promising results, the question remains whether the elaborate procedures described here produce estimates of the spatial distribution of crops that are better than other approaches used at this scale of analysis. We examined three possible short-cut methods for assigning state level crop areas into municipios: (1) in proportion to the total land area of the municipios, (2) in proportion to the cropland area of each municipio, and (3) in proportion to the amount of (biophysically) suitable land for the production of each crop in each municipio. This last approach has several options since suitability surfaces are generated for specific production systems. We thus made four allocations of state level crop area into municipios: (a) in proportion to the area suitable for low-input rainfed production, (b) in proportion to the area suitable for high input production, (c) in proportion to the areas suitable for irrigation in each municipio, and (d) in proportion to the (weighted) area suitable for low-input, high-input and irrigated production in each municipio. Table 3 shows the variance in municipio crop areas explained by each of the approaches, including the CE approach. For all crops, the CE approach was most successful in predicting municipio crop areas – and in the cases of wheat and beans, by quite a large margin. The simplest procedure, distributing the crop production in proportion to municipio total areas, was the second best method for maize and beans, whose broad geographic production base reflects the ubiquitous demand for these primary food (and in the case of maize, feed) commodities in Brazil. This approach is least successful in predicting the production distribution of wheat, rice and soybeans, all of which have more restricted agroecological ranges (wheat and rice), or are predominantly grown by large-scale commercial enterprises in the "cerrados" region (wheat and soybean). Conversely, apportioning crop production uniformly across the cropland extent, was the second best predictor for wheat and soybean, likely because both crops are grown commercially in extensive tracts of land that are easily detected as cropland by satellite sensors. The cropland proportion was least successful for beans, perhaps because it is often a home-garden crop or grown in other complex cropping systems that are much more difficult for satellite sensors to discriminate as cropland. Predictions based on the high-input or "mixed" suitability data were better than those based on the low-input and irrigated suitability data. The four suitability surfaces were second best predictors only twice, once for rice and once for cassava.

6. FINAL REMARKS

We have proposed a spatial allocation model for crop production statistics based on a cross-entropy approach (CE). The approach utilizes various information sources such as satellite imagery, biophysical crop suitability assessments, and population density, in order to generate plausible, disaggregated estimates of the distribution of crop production on a pixel basis. In the application of the spatial allocation model to Brazil, a comparison of actual *municipio* production statistics with synthetic *municipio* estimates - generated from pixel level disaggregating of state level statistics - yielded R^2 values between 0.4 and 0.65. For each crop the CE model approach performed better than other commonly used short-cut methods for disaggregating production statistics.

Amongst other things, the encouraging results suggest that remote sensing and image processing data and tools could be used more extensively in helping to explore the spatial heterogeneity of agricultural production, although improved discrimination of subsistence farming and smaller, mixed production plots is needed. On the other hand, working at a spatial scale of individual pixels creates many data management and computational challenges. Some of these challenges need to be met through improved numerical methods and mathematical optimization tools.

Although the current model provides promising results, more work is underway to improve its performance. The first-best solution is to compile more, and more spatially disaggregated production data, especially linked to information on specific production technologies. National household or agricultural survey data (particularly geocoded data) on the location and quantity of crop production provide direct observations of the crop distribution surfaces. But compiling such data is expensive in an international context. Other means of improving the crop distribution priors include improved representation of existing variables (such as cropland extent and crop suitability), addition of other conditioning variables, and improved algorithms to transform these data layers into priors. Such options include using higher-resolution, and better ground-truthed land cover data for delineating cropland, particularly in extensive, low intensity systems and in more humid tropical areas where seasonal vegetation changes are less pronounced. We can likely do more to improve the utilization of data on population, slope and physiography, and transportation networks in helping predict crop production patterns.

One interpretation of our results is that rules for generating the prior distributions should be crop specific. While the crop suitability surfaces are, by definition, crop specific, they contain no behavioral information about the likelihood that a crop will actually be grown in a particular location. Clearly, factors such as local food security, farmgate prices, transportation costs (affected by the bulk density and perishability of individual commodities) and the spatial configuration of key markets, also shape the commodity production decisions of farmers. Better information on (multi-)cropping patterns would allow us to, say, allocate maize and beans together in the same location and to apply the proper cropping intensities if we know that maize followed by beans in a single season is the predominant mode of cultivation. Developing and testing commodity-specific decision rules and collecting data on major cropping patterns so as to enrich the generation of priors are likely cost-effective next steps, as is the examination of better ways of capturing expert and local knowledge about production patterns.

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